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A generalized dynamic discrete choice model for green vehicle adoption

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ABSTRACT

Much is happening in the automotive industry and new models are in the market or are expected to be available soon. At the same time, environmental awareness, new regulations for increased fuel efficiency, and the need to diminish greenhouse gas emissions make small vehicles and alternative fuel vehicles more competitive. As a consequence, vehicle characteristics and consumer decisions will change rapidly in the short and medium run. Accounting for the dynamic of the problem is important to correctly forecast green vehicle acceptance and to evaluate eco-friendly policies. This paper proposes a generalized dynamic discrete choice approach that models purchase behavior and forecasts future preferences in a finite time horizon setting. The framework allows one-time purchases, repeated purchases, univariate and multivariate diffusion processes that capture the evolution of vehicle characteristics and dynamics in the market conditions. The models proposed are estimated using stated preference data collected in Maryland. Results show that the formulation with repeated purchases successfully captures changes in the market shares, and that the multivariate diffusion process adopted to model the evolution of fuel prices further improves both model fit and the ability to recover peaks in demand. The estimated coefficients have been applied to test different policy scenarios, including changes in fuel prices, vehicle purchase prices, and improvements of car characteristics. These policies have a high impact on the adoption of electric cars and on their diffusion in the marketplace.

1. Introduction

The choice of a specific durable good is not only influenced by the characteristics of the good itself, but also by industry evolution, development of new technology, government regulation, an individual's social network, change in personal attitude, etc. (Lorincz, 2005). In the context of vehicle purchasing, consumer behavior highly depends on fuel price and its volatility (Goodwin et al., 2004), innovations in the vehicle market (Schiraldi, 2011; Cirillo et al., 2015), increasing awareness about environmental issues (Flamm, 2009; Flamm and Agrawal, 2012), friends' and families' travel behavior (Farber and Páez, 2009), and policies and taxes introduced by local and national authorities (Hayashi et al., 2001; Feng et al., 2005). In recent years, more fuel-efficient vehicles or alternative energy sources are available in the market and their characteristics are expected to change over time as technology develops. Considering that vehicle characteristics evolve rapidly with time, consumers choose to buy a vehicle or not in order to maximize the expected utility over the current and future periods (Cirillo and Xu, 2011). However, in transportation planning, static models are usually used to estimate vehicle ownership and type, ignoring the dynamics in vehicle attributes and the evolution of taste and preferences. Therefore, a dynamic framework is necessary to model vehicle purchase behavior, especially adoption of more efficient

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vehicle or vehicle running on alternative fuels.

Dynamic discrete choice models (DDCMs) of demand for durable goods were started by researchers in economics and social science. Rust (1987) was the first to formulate a dynamic logit model by proposing a method based on dynamic programming. His model was applied to estimate the optimal stopping time to replace a used bus engine. Melnikov (2013) expanded the engine replacement model to capture the purchasing behavior of printer machines. He applied the optimal stopping problem to model the decision of whether to buy a printer machine or to postpone the purchase based on the expected evolution of the product quality and price, incorporating consumer heterogeneity and considering inter-temporal incentives of market participants. Recently, Cirillo et al. (2015) introduced a dynamic discrete choice formulation for vehicle ownership analysis. Specifically, the proposed structure intends to capture not only the optimal purchase time but also consumer's choices on vehicle types in a dynamically changing vehicle market. They formulated the timing of consumer's purchase decision as a regenerative optimal stopping problem. The model explicitly accounts for consumer's forward-looking behavior and market evolution such as the changes in gasoline price or electric vehicle price. However, their model is limited to repeated purchases, and is only capable of incorporating one evolving dynamic attribute at a time.

The work proposed in this paper generalizes the DDCM of Cirillo et al. (2015) and presents three major innovations. First, the proposed model is able to capture the purchase pattern of different durable goods in the market, allowing for both one-time purchase (agents are out-of-market once a purchase is made) and repeated purchases (agents are always in the market). Second, it relaxes the assumptions on the number of forward-looking time periods. Last, to model the industry evolution the proposed model incorporates a stochastic diffusion process that accounts for multiple interdependent attributes changing over time. The approach contributes to the state of the art by modeling jointly vehicle purchase time and vehicle type choice in a finite time horizon. The proposed DDCM is estimated on the data from a web-based stated preference survey which was designed to analyze households' future vehicle preference in the Maryland area.

The remainder of this paper is organized as follows. Section 2 reviews the previous literature on DDCMs with applications in economics and transportation. Section 3 presents the methodology and formulates the dynamic structures for different scenarios: one-time purchase, repeated purchases, one evolving attribute, and multiple interdependent evolving attributes. Section 4 introduces the stated preference panel data for model estimation, while Section 5 presents model estimation results. Model validation and sensitivity analysis are given in Section 6. The final Section offers concluding remarks and avenues for future research.

2. Literature review

2.1. DDCMs in economics

DDCMs are widely used in economics and related fields. They are useful tools for the evaluation of price elasticity, intertemporal substitution, and new policies in durable goods markets. In the structure of DDCMs, agents are forward-looking and maximize expected intertemporal payoffs, with the knowledge of the evolving nature of product attributes such as price and technology. The earliest generation of research on DDCMs includes Wolpin (1984) on fertility and child mortality, Miller (1984) on job matching and occupational choice, Pakes (1984) on patent renewal, and Rust (1987) on machine replacement. Although the computational complexity of model estimation represents a clear impediment to the development of these dynamic structures, a significant number of interesting applications aiming at solving the empirical issues have appeared in different areas of economics, e.g., permanent unobserved heterogeneity, initial conditions, censored outcomes and sample selection, measurement error, endogeneity, identification, etc. (Aguirregabiria and Mira, 2010).

With his pioneering work in dynamic modeling, Rust (1987) was the first to formulate the optimal stopping problem and to estimate the optimal time to replace a bus engine. The model was conceived for a single agent, a homogeneous product, and infinite time horizon; random components were assumed to be additively separable, conditionally independent and extreme value distributed. Melnikov (2013) expanded Rust's model to consider a binary decision, whether to buy or to postpone the purchase, based on the expected evolution of printer's quality and price. In his dynamic structure, Melnikov considered heterogeneous products and homogeneous consumers. He assumed that consumers will be out-of-market once they make a purchase, and random components are independently distributed over consumers, products, and time periods. Lorincz (2005) extended the Rust model by proposing the so-called persistent effect, which allows consumers who already had a product to upgrade it instead of replacing it.

Knowing the importance of incorporating consumer heterogeneity, the dynamic structure was further improved in a series of later papers (Berry et al., 1995; Shcherbakov, 2016; Carranza, 2010; Gowrisankaran and Rysman, 2012; Dubé et al., 2012). Berry et al. (1995) showed that it is necessary to consider consumer heterogeneity to obtain realistic predictions of elasticity and welfare. Their model includes random coefficients, accounts for market-level demand shocks, and endogenous prices, but is static in nature. Dubé et al. (2012) recast Berry's estimation as a mathematical program with equilibrium constraints to avoid numerical issues associated with the standard nested fixed point (NFP) algorithm and to make the estimation process more efficient. Gowrisankaran and Rysman (2012) analyzed consumer's preferences over digital camcorder products by combining Berry's modeling techniques of consumer heterogeneity and Rust's optimal stopping technique. Their model explicitly accounted for dynamics in consumer behavior and allowed for unobserved product characteristics, repeated purchases, endogenous prices, and multiple differentiated products. Another interesting extension of Rust's bus engine replacement model was the integration of an auto-regressive process of order n (AR(n)) type serial correlation of error components into the dynamic structure (Reich, 2013). To make the estimation process more efficient, Reich (2013) decomposed the integral over the unobserved state variables in the likelihood function into a series of lower dimensional integrals, and successively approximated them using Gaussian quadrature rules. More recently, DDCMs have been